A Multi-Level, Hierarchical Approach to Technology Selection and Optimization

Janel N. Nixon* and Prof. Dimitri N. Mavris†
Aerospace Systems Design Laboratory
School of Aerospace Engineering
Georgia Institute of Technology
Atlanta GA 30332-0150

Abstract

Advances in performance and increases in revenue are most often facilitated by the development and application of new technologies. Recent efforts in multidisciplinary design have yielded methods for the evaluation and selection of technologies in the presence of uncertainty. Many of these methods aim to forecast the impacts of new technologies amidst the uncertainties associated with technology performance and operating conditions. These forecasting abilities aid in the selection of the technology that gives the highest probability of success. Many methods offer efficient probabilistic assessments that allow the designer to extract the optimal solution. However, a single optimal solution may not be sufficient for systems that are heavily influenced by operating conditions. All aerospace and industrial power systems are influenced by at least a few parameters such as air density, pressure, temperature, humidity, etc. For instance, power plant output fluctuates significantly with changes in ambient conditions. In order to evaluate proposed technologies for such a system, a new approach is needed in order to define a framework where operational uncertainties may be quantified and modeled.

A robust design methodology has been developed, whereby operating conditions and their impacts can be modeled easily and accurately. An industrial gas turbine power plant is used as an example, and the proposed methodology is integrated with existing methods developed by Mavris and Kirby[1] in order to predict the overall impact of a technology over a yearlong period of operation in a specified region. This paper demonstrates how to use this model to refine the design of the technology. Hence, the technology development is treated as a suboptimization problem in which the optimum design settings of the technologies are found. This ambient model is then used to forecast the impact of each technology. Finally, these results are then used to select the most promising technology for implementation into the final design.

Motivation

The demand for electricity is expected to grow 1.7 percent annually until 2020. This projected growth is the result of the combination of the rising number of households, growth in commercial floorspace, and increase in industrial output. In addition, observations show that climatic temperatures are slowly increasing, along with the duration of these high-temperature periods. The steady rise in demand, along with climbing temperature extremes will create a need for increased peaking capacity. With the onset of the summer months, cooling usage increases, and the demand for power escalates. At the same time, the warmer air reduces the efficiency of power plants, causing a reduction in available power output. Thus, the growing demand and reduced efficiency are expected to increase the peak-to-average load ratio for utilities, thereby creating the need for power-enhancing alternatives that provide additional "peaking" capacity.[2]

Combined-cycle power plants are among the most economical systems used to generate electricity. Consequently, they are expected to play a major role in meeting increasing demands. These predictions, along with the large volume of combined cycle sales in recent years, have boosted research and development of performance-enhancing technologies. Many of these technologies aim to increase power output solely during peak summer demand. In other words, these technologies are often designed to be turned on only when the temperature exceeds a certain value. Throughout the remainder of the year when temperatures are lower, the technology will be turned off, consequently inducing a small loss in efficiency of the system.

Given this situation, the performance of the power

* Graduate Research Assistant, AIAA Student Member
† Professor, Director ASDL, Boeing Chair in Advanced Aerospace Systems Analysis, Associate Fellow AIAA

plant and any technology improvements to the power plant will be highly dependent on operating conditions. Hence, a technology may provide a significant benefit in a warm region, and at the same time degrade performance in a cooler region. As a result, the designer is faced with a situation in which the optimal design is no longer a single formula, but a variety of designs that must be tailored to the individual customer. This type of trade-off is an ever-increasing phenomena within aerospace and power generation industries, in which system performance is often influenced by changing operating conditions. In turn, there is a need for a method that will provide the designer with the ability to easily assess the impact of operating conditions on technology performance. This method must allow the designer to forecast these operating conditions quickly and accurately, while also accounting for uncertainties. In combining these capabilities with a preexisting decision-making methodology, the designer can deliver solutions that are tailored to individual customer.

Background

During the summer months when the air is warmer and less dense, there is a reduction in mass flow through a gas turbine engine, causing a decrease in power plant efficiency, and consequently, a decrease in power output. Many new developments in power-enhancing technologies aim to thwart reduced efficiency by cooling inlet air during these peak periods. One way to do this is to mix water with the inlet air. The water will evaporate and reduce the ambient temperature down to the wet-bulb temperature, or the lowest temperature that can be achieved by saturating the air.[3] There are several techniques that can be used to introduce water into the inlet air; two such techniques are evaluated in this paper, both of which are variants of evaporative cooling technologies. The main difference between the two is that one uses a wetted-honeycomb media to release water as air passes through, and the other uses an array of nozzles to spray atomized water into the inlet.[4, 5] Both technologies use relatively simple concepts, but these concepts are greatly complicated by the fact that the maximum amount of water that can enter the inlet is dictated by the ambient conditions. If the relative humidity is already high, the technologies will not be as effective. In addition, if the air becomes oversaturated, the water droplets will coalesce, causing excessive corrosion and / or erosion of the compressor hardware. For these reasons, careful attention must be given to the ambient conditions, particularly temperature and humidity. The proposed method not only addresses the technology's dependence on operating conditions, but also the uncertainties associated with the drawbacks of an increased number of parts and risk of accelerated corrosion.

Approach

The goal of the methodology is to provide a framework where alternatives can be evaluated, and the probability of success of each alternative can be quantified on a case-by-case basis. This method is a multi-level, hierarchical approach that not only allows the evaluator to identify the most promising alternatives, it also allows the designer to adjust the technology settings to achieve optimum technology performance. These attributes allow the method to be used as either a preliminary design tool or a technology selection tool, or both. As a preliminary design tool, the method can be used to model the operating conditions, and then optimize the design of the technology for those forecasted conditions. As a technology selection tool, the method can be used, again, to model the operating conditions, and then to select the technology that will give the customer the greatest probability of achieving a given goal. The proposed method addresses individual customer requirements using the twelve steps depicted in Figure 1.

Step 1: Define the Problem

As in any decision making process, the first step is to formulate the problem by identifying an objective. There are several tools available for formally mapping requirements based on the customer's economic or performance needs. Quality Function Deployment (QFD) is a widely used tool for mapping customer requirements, and it is most advantageous when the customer desires a large number of design characteristics or attributes. In these cases, QFD allows the designer to establish an Overall Measure of Value (OMV) for each of the customer's wants or needs. For this reason, QFD is highly recommended for the problem definition phase of any process involving multiple objectives.[6] For the example investigation described in this paper, it is assumed that the only objectives are to maximize the power output and net revenue generated by the combined-cycle power plant, so QFD is unnecessary here.

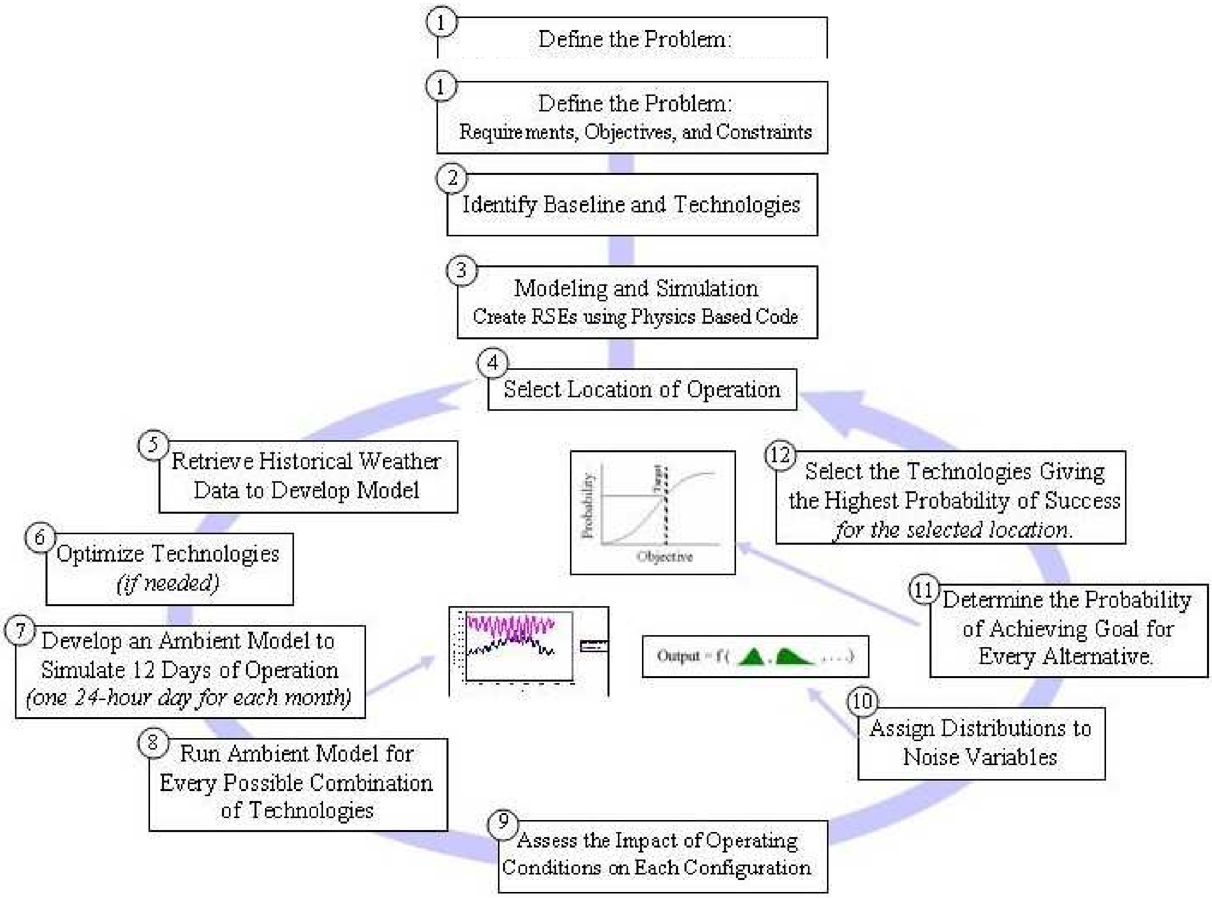


Figure 1: Method for Selecting Technologies in the Presence of Operational Uncertainty

Step 2: Identify Baseline and Technologies

With the objectives defined, the next step is to identify the baseline and any technologies that might make a beneficial addition to the baseline. If the baseline is not a fixed design, and the designer wishes to investigate several design alternatives, then they may refer to the first five steps of the method for Technology Identification, Evaluation, and Selection (TIES).[1] After the baseline is defined, the technologies must also be specified. If the technologies are in the developmental phase, or if the technology settings are variable, the investigator may wish to optimize the technology settings. A "technology setting" refers to any physical parameter that may affect technology performance. For example, as applied to this problem, a technology setting might be the number of nozzles used to spray water, or the thickness of the wetted-honeycomb media. These are the technology design variables that can be changed until an optimum setting is found.

Step 3: Modeling and Simulation

Whether the technology settings are variables or the technologies are pre-defined, a modeling and simulation environment is needed to assess the technology impacts. A modeling and simulation tool may consist of any combination of sizing/synthesis codes, physics-based analytical tools, or metamodels. For complex analyses, it may be beneficial to use a Design of Experiments (DoE) to create Response Surface Equations (RSEs) to model the complex system. An RSE is a form of a metamodel of the system performance, and its use has widespread applications in engineering design.[7, 8] In addition to Response Surface Methodology (RSM), there are several existing techniques available for simplifying complex models, and in some cases, a metamodel may be completely unnecessary if the model is already fast enough. For this example, RSEs are used in place of a complex code, allowing for efficient exploration of DoEs.

At this point in the method, the initial DoE should only include those design variables that represent the technology settings that are being varied. It is also important for the DoE to include a switch that determines whether or not the technologies are installed, and whether or not they are being operated if installed. It is assumed that the designer already knows which technologies are compatible, so any cases that do not represent feasible technology combinations should be eliminated from the DoE. If the technology settings are fixed, then the DoE should be composed only of installed / uninstalled switches for the technologies such that each case represents a compatible combination of technologies.

It should also be noted that in the modeling and simulation environment, it is imperative for the user to have the capability to input or alter the operating conditions. If the system performance is truly dependent upon the operating conditions, then an adequate model must account for these conditions when computing performance outputs.

Step 4: Select Location of Operation

The design space exploration begins with the selection of the location of operation. If the technologies are in the conceptual design phase of development, or the Technology Readiness Level is low, it may be beneficial to select a region in which the technologies will most likely provide a benefit to the baseline system. In doing so, the designer can gauge the likelihood of success for each technology. For the problem at hand, the proposed technologies will best perform in hot, arid operating conditions in which saturation of inlet air will have the greatest effect on the temperature of the air entering the engine. If a preliminary assessment is performed using a hot and arid location, and the addition of technologies gives no advantage over the baseline design, then one may conclude that the technologies will not provide any gain at all. If these kinds of results are observed, it may be best to advise the manufacturer to discontinue research and development on those technologies that show a low probability of success.

It is also possible that the technologies are in the final stages of development, and the manufacturer would simply like to advise a customer at a given location. If a customer is planning to buy a certain system, then they may wish to know which technologies can be added to that system to provide optimum performance, and / or revenue for their individual situation. This methodology is extremely flexible, so it can also be applied to the rare situation in which a technology has variable settings that can be easily altered. For example, what if the number of spray nozzles in an inlet conditioning technology is a variable? It is known that the relative humidity plays a role in determining the maximum amount of water that can be evaporated into the air. Consequently, fewer nozzles may be needed in a humid region, where the danger of oversaturation is greater. For the demonstration provided in this paper, Phoenix Arizona is selected to represent a hot, arid region in which the system is being evaluated.

Step 5: Retrieve Historical Weather Data

Retrieval of data is one of the easiest parts of this method. Once the information is located, the main task is simply compiling the data into a useable form. A wealth of historical weather data is available for a large number of cities in the United States.[9] For this method, historical monthly averages are used to build the weather model. In particular, the reference source provides hourly averages of ambient weather conditions by month. Thus, for every month, the average ambient conditions are given for every hour in the day. A sample of these data is given in Table 1. Data are available in this form from 1996 to the present, so these values can be averaged over a number of years to give a more robust model. Thus, for the city of interest, the evaluator must retrieve Table 1 for every month for at least one year. For a more robust model these tables may be compiled for several years, and each hourly value can be averaged over the number of years for each month. Whether the data is only taken from one year, or averaged over several years, the final model will consist of 288 data points, where each data point represents averaged ambient conditions for one hour of one month. In other words, Table 1 is representative of a typical day in May in Phoenix, Arizona. Since Table 1 gives 24 data points (one for each hour of the typical day), then the twelve months will give a combined 288 data points. For the example problem being evaluated in this paper, ambient temperature and relative humidity have the most significant effects on the system, so only these data points are extracted and compiled.

Step 6: Optimize Technology Settings

This step is optional, and should only be included if either technology development is still in the conceptual design phase, or if the technology is mature and the manufacturer still maintains some control over the design settings. If, on the other hand, the technology is mature and the design is completely fixed, then this step should be omitted from the analysis.

SUMMARY BY HOUR

HOUR (LST)	CEILOMETER	EFF CLD AMT	DRY BULB	DEW POINT	WET BULB	RELATIVE HUMIDITY	PRESSURE (INCHES,HG) STATION	PRESSURE (INCHES,HG) SEA LEVEL	VISIBILITY (MILES)	WIND SPEED (MPH)	RESULTANT WIND (MPH) SPEED	RESULTANT WIND (MPH) DIRECTION
01			60	23	45	26	28.79	29.94	10.00	5	1	12
02			58	23	44	28	28.79	29.94	10.00	6	3	10
03			56	23	43	30	28.79	29.94	10.00	5	2	9
04			56	23	42	31	28.79	29.94	10.00	6	2	9
05			55	23	42	32	28.79	29.95	10.00	6	3	8
06			53	23	41	33	28.81	29.96	10.00	5	3	10
07			53	23	41	34	28.82	29.98	10.00	5	3	10
08			56	23	43	29	28.84	30.00	10.00	5	3	11
09			61	22	45	25	28.86	30.01	10.00	6	2	8
10			64	22	46	22	28.86	30.01	10.00	7	1	8
11			68	23	48	20	28.85	30.00	10.00	6	1	14
12			71	23	50	18	28.84	29.99	10.00	6	2	23
13			73	24	51	17	28.81	29.96	10.00	7	2	27
14			75	24	52	16	28.78	29.93	10.00	7	4	24
15			76	24	52	16	28.76	29.91	9.77	8	5	26
16			76	24	52	15	28.75	29.89	10.00	10	7	27
17			76	23	52	15	28.74	29.88	10.00	9	8	26
18			75	23	51	15	28.74	29.88	10.00	10	8	27
19			73	23	51	16	28.74	29.89	10.00	9	7	27
20			71	22	49	17	28.76	29.91	10.00	8	5	27
21			68	23	48	19	28.77	29.92	10.00	7	3	26
22			66	23	48	21	28.78	29.93	10.00	6	3	26
23			64	23	47	24	28.79	29.94	9.97	7	1	31
24			62	24	46	26	28.79	29.94	10.00	7	1	24

(AVERAGES: columns Ceilometer through Wind Speed)

Table 1: Hourly Averages of Weather Conditions in Phoenix, Arizona from March, 2002[9]

For this investigation, it is assumed that for the first technology, the manufacturer can vary the number of spray nozzles that are installed. Likewise, for the second technology, it is assumed that the manufacturer has control over the thickness of the evaporative media that is installed in the system. For this particular example, it may not be realistic to assume that the manufacturer can vary these settings for every single product sold. Nonetheless, the situation is simulated for the sake of argument, in case a similar situation should arise. Given these assumptions, the initial DoE that was obtained in the third step is given in Table 2. In this DoE, a technology setting of '1' indicates that the technology is added to the baseline design, and a '0' implies that the technology is not present. The two technologies are not compatible, so there are no runs in the DoE that include both of the technologies into the design. In addition, the nozzle count and media thickness have been normalized so that a '1' represents the maximum number of nozzles or media thickness, a '-1' represents the minimum number of nozzles or media thickness, and a '0' is the value between the maximum and minimum. The first run is included to simulate the baseline (with no technologies) performance in the selected location.

The next step is to simulate the effect of operating conditions on each case in the DoE. This can be

Run	Technology 1	Nozzle Count	Technology 2	Media Thickness
1	0	NA	0	NA
2	1	1	0	NA
3	1	0	0	NA
4	1	-1	0	NA
5	0	NA	1	1
6	0	NA	1	0
7	0	NA	1	-1

Table 2: Initial DoE of Configuration Options

accomplished using a Taguchi analysis, in which the operating conditions can be treated as noise variables that are applied to the DoE, which will act as the inner array in the Taguchi analysis.[6] For this step, Crystal Ball can be used to fit a distribution to the data obtained in the previous step. The resulting distributions obtained for this example are shown in Table 3.

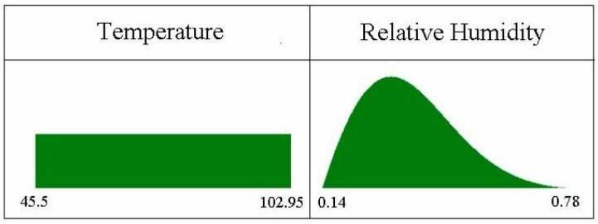


Table 3: Yearly Distributions in Temperature and Humidity

If the data from step 5 are plotted as a function of time, it becomes apparent that temperature and humidity are extremely dependent upon one another. Figure 2 displays a plot of these data for Phoenix, Arizona. In this plot, for the temperature line, each peak essentially represents an average noontime temperature for each month. There are twelve peaks in all, one representing each month of the year so that the first rise and fall represents a typical day in January, the second depicts a typical February day, etc. In this step, temperature and humidity are simply treated as noise variables, so any coupling between the two is ignored. Though it is evident in Figure 2 that the coupling is significant, the technology settings may be optimized with sufficient reliability using the uncoupled noise variable distributions shown in Table 3. If the Taguchi analysis is applied to the DoE using Crystal Ball, the output is a series of Cumulative Distribution Functions (CDF). Each CDF represents the distribution of results obtained by applying the temperature and humidity distributions to one run of the DoE. On each CDF, the response is plotted on the horizontal axis, and the vertical axis gives the probability of achieving a value that is less than a certain response. Hence, the rightmost value on the horizontal axis is the maximum possible output value, or the value under which one-hundred percent of the output values will lie. Table 4 shows the CDFs obtained from this analysis, where the output being tracked is the normalized power output from the power plant. At this point, there is no sense in tracking net revenue, because the noise variables have not yet been accounted for. Thus, if there were no uncertainties, the maximum power output would equate to maximum net revenue, so there is no need to track both outputs for this step.

The CDFs in Table 4 depict the forecasted distribution for power output for each configuration. The mean values labeled in Table 4 represent the value at which there is a fifty-percent chance of generating at least that much power. These values are normalized against the mean power output for the baseline, so that a mean value greater than one indicates an increase in output over the baseline. In essence, these CDFs predict the variations in performance of each configuration. For instance, if an observer recorded the power output of the second configuration at random intervals ten times each day for an entire year, the data would look like the CDF for the second run in Table 4. Consequently, the mean values depicted in Table are simply approximations of the average value of normalized power output for an entire year. From the first three runs, the CDF that gives the highest mean (and possibly the lowest deviation) describes the best setting for nozzle count. The best run out of the second set of three gives the best setting for the media thickness. From Table 4, it is evident that the optimum settings for nozzle count and media thickness are the maximum possible values (runs 2 and 5). If, on the other hand, the center-point of the design variable (run 3 or 6) is the best out of the set of three, then the actual optimum lies somewhere within the variable range. However, this optimum may not actually be the center point. In this case, a Monte-Carlo simulation or an optimization scheme is needed to locate the actual optimum value. These procedures are described in more detail in References.[7, 8] A new DoE is formed using the optimized settings, and this new DoE is shown in Table 5. These settings only reflect the optimum settings for the operating conditions that were modeled for Phoenix, Arizona. It is possible that the optimum settings will be different for a different region.

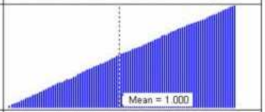
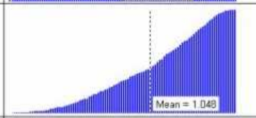
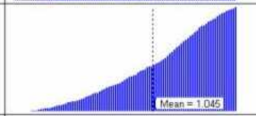
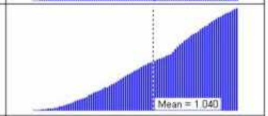
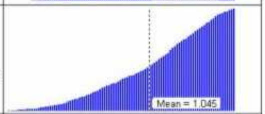
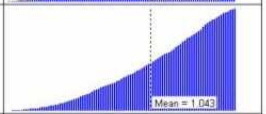
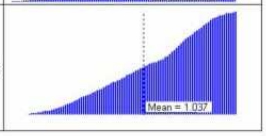
Run	Cumulative Distributions Normalized Power Output
1: Baseline	
2: Baseline + Technology 1 with maximum nozzle count	
3: Baseline + Technology 1 with median nozzle count	
4: Baseline + Technology 1 with minimum nozzle count	
5: Baseline + Technology 2 with maximum media thickness	
6: Baseline + Technology 2 with median media thickness	
7: Baseline + Technology 2 with minimum media thickness	

Table 4: Cumulative Distribution Functions for Normalized Power Output

Step 7: Develop an Ambient Model to Simulate Twelve Typical Days of Operation

The 288 data points that were compiled in step 5 are used to model the operating conditions. At this point, the coupling between the temperature and humidity must be taken into account. The final goal of this method is to find reliable estimates for the outputs. In order to do so, the relationship between temperature and humidity must be accounted for. If temperature and humidity are treated as noise variables, as they were in step 6, then any interactions between the two would be neglected, and impossible combinations of the two would be incorporated into the analysis. In order to incorporate these interactions, the 288 data points are used to form a table of experiments. Since this table represents a model of the ambient conditions, the output from every run will be averaged to find the value that will be used to approximate the yearly average for that output. A simple script is needed to execute the 288 runs in

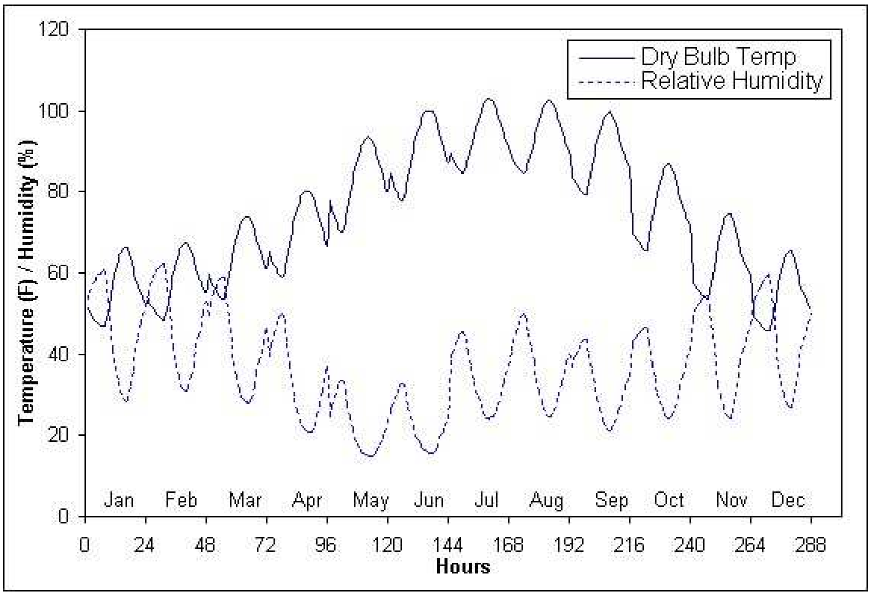


Figure 2: Annual Fluctuations in Temperature and Humidity in Phoenix, Arizona

Configuration	Technology #1	Nozzle Count	Technology #2	Media Thickness
1	0	NA	0	NA
2	0	NA	1	1
3	1	1	0	NA

Table 5: DoE of Optimized Technology Settings

the table, and again, it is recommended that RSEs be used to approximate the results if the analysis code is complex. For this example, a simple Visual Basic script was written to allow the full analysis to be executed within Excel.

Step 8: Run Ambient Model for Every Combination of Compatible Technologies

A Taguchi analysis is again used to assess the impact of the operating conditions. Only this time, the inner array is the new, smaller DoE that was found in step 6 given by Table 5, and the outer array is the 288-run ambient model instead of the uncoupled distributions. At this point, both power output and net revenue must be accounted for. These outputs are recorded for every run in the ambient model, giving 288 values for power output and revenue for each possible configuration given in Table 5. Using the results, the power output from each configuration is plotted as a function of temperature, as shown in Figure 3.

In Figure 3, the power output is plotted against temperature, but the fluctuations in humidity are also affecting the data. It is the humidity that causes the data to fluctuate when the technologies are employed, implying that technology performance is influenced by humidity, as expected. Thus, the smooth line for the baseline indicates that the baseline output is not overly sensitive to changes in humidity. For those configurations with a technology addition, any data points that occupy the space above the baseline curve represent gains with respect to the baseline. All data points below the baseline curve imply losses from the baseline design. For the two technology lines, a step in power output occurs at 59 degrees, when the technology is turned on. Below that temperature, the technologies are installed, but are inactive, causing a small loss in efficiency. The extent of the losses and / or gains is indicative of the amount of time that the system spends operating under or over 59 degrees. Effectively, the main objective of the proposed method is to find out whether or not the gains will outweigh the losses. However, the plot in Figure 3 does not provide a sufficient prediction of power plant performance, because there is

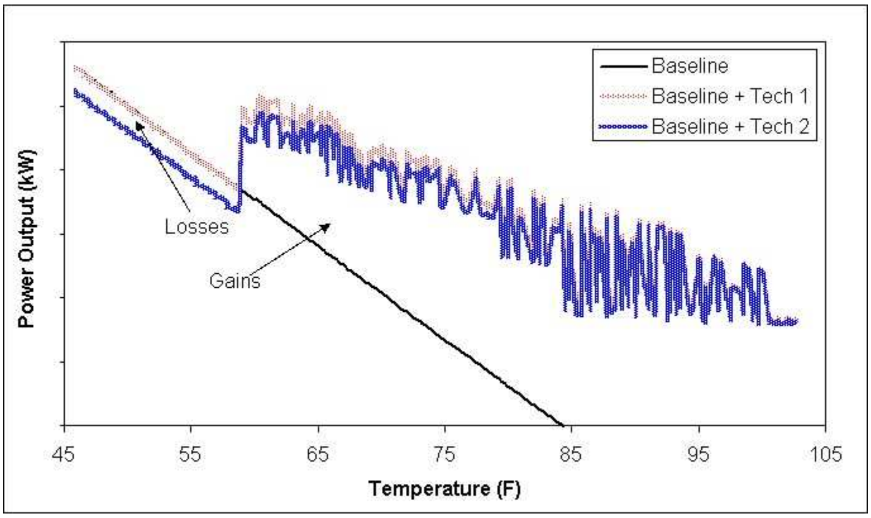


Figure 3: Plot of Power Plant Output for the Range of Temperature and Humidity Values in Phoenix, Arizona

still a great deal of uncertainty which has not yet been accounted for.

Step 9: Assess the Impact of Operating Conditions on Each Configuration

Taking the percent difference between the hourly output for the baseline and the baseline plus the technology will give an approximation for the technology impacts. These impacts are simply estimates of the effects that a technology will have on a certain output. For this problem, this impact is quantified as a percent increase or decrease from the baseline output. However, each of these technology impacts applies only to the operating conditions for which it was found. Unlike most technology selection methods that assume the technology has a direct impact on the output, this method accounts for the direct impact of operating conditions on the technology performance. In other words, the actual impact of a technology is determined by the ambient conditions in which it is operating. In order to quantify the technology impact over the range of operating conditions, the outputs from each configuration are obtained for each case in the ambient model. Since there are 288 cases in the ambient model, there will be 288 outputs corresponding to each configuration. The technology impact for each case is obtained from the percent difference between the output from the baseline alone, and the baseline with an added technology. Thus, there will be 288 of these percent differences to describe the overall impact each technology. In other words, values for power output and revenue have been obtained for every hour in the 12-day model for all three configurations. The overall impact of the operating conditions on the technology may then be modeled by fitting a distribution to the 288 differences. These distributions capture the variations of the technology impacts as they fluctuate with operating conditions. Figure 4 outlines the procedure used to generate a distribution on a technology impact for an arbitrary response, such as power output or revenue. These technology impacts are essentially noise variables, because there is a certain level of uncertainty associated with new technologies and / or the analyses used to model them. Even the most complex code can not precisely predict how these new technologies will affect downtime, part corrosion, and therefore revenue. Therefore, these technology impact distributions account for the fact that technology impacts are a function of operating conditions, with an associated uncertainty. Even though uncertainty is being accounted for, it is important to remember that the resulting distributions are only valid for the location being evaluated. These distributions will change significantly when operating conditions change, so they must be recalculated for any new location with significantly different operating conditions.

Run	Response from Baseline Configuration	Response from Configuration with Additional Technology	Percent Difference Between Baseline and Configuration with Additional Technology
1	9360.2	9921.8	+6%
2	8992.6	9981.8	+11%
3	9147.3	8964.4	-2%
:	:	:	:
:	:	:	:
288	9487.9	10341.8	+9%

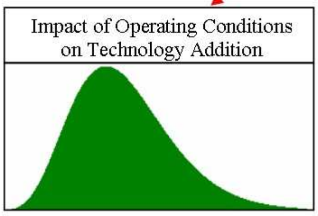


Figure 4: Method for Finding Technology Impact Distributions Due to Operational Uncertainty

Step 10: Assign Distributions to Noise Variables

At this point, noise variables are the only items still unaccounted for. These noise variables are any parameters that affect the output, and have some uncertainty associated with their values. For instance, fuel cost, hours of operation, and maintenance costs are all parameters that have an associated uncertainty. It is likely that, based on historical data, the designer has a good estimate for each of these values. These historical data may be used to fit a distribution to variables such as fuel cost and the base value of energy. On the other hand, the designer may rely on pure intuition to assign distributions to variables like the number of hours of operation in one year. An experienced designer will be aware that with the addition of one of the proposed technologies, the number of parts will increase as will the likelihood of accelerated corrosion. Thus, the increased maintenance requirements will most likely cause the number of forced outages to increase, and therefore the total hours of operation will decrease. However, the designer can not predict the exact amount by which the hours of operation will decrease, or if there will even be a decrease at all. Hence, there is a great deal of uncertainty associated with the hours of operation. To account for this uncertainty, the most logical distribution is one that has been shifted to the left of the estimated value to account for the probability that the added technology will reduce the hours of operation. The resulting distribution for hours of operation is shown in Table 6, along with the other distributions that were incorporated into this analysis. The technology impact distributions that were generated in the previous step are included among the noise variables, since there is some uncertainty associated with the technology impacts.

Step 11: Determine the Probability of Achieving the Goal for Every Alternative

A Taguchi analysis is used to apply the distributions from step 9 to the reduced DoE from step 6, and again, the end result is a collection of CDFs. These CDFs are the culmination of thousands of random trials where the values of each of the noise variables are randomly selected from the uncertainty distributions from step 10. The output values are extracted from each of these trials, giving a histogram where the vertical axis is the frequency of occurrence, and the horizontal axis is the range of values of the selected output. If this histogram is converted to a CDF, the vertical axis will give the probability of achieving a specified value for the output. If the customer has a specific goal in mind, then the technology selection is based on the probability value of that metric for the specified target value on the CDF. The configuration with the highest percent confidence of achieving the metric target is considered to be the "best" configuration. If the customer has more than one objective, the best configuration may not be readily obvious upon a first inspection of the CDFs. In this case, it may be necessary to use an evaluation tool such as a Pugh Evaluation Matrix in conjunction with a decision-making technique such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).[1]

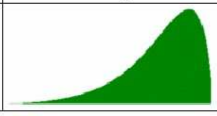
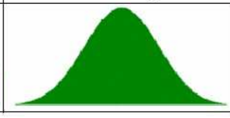
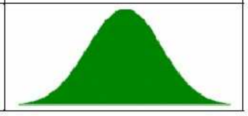
Base Value of Energy	Fuel Cost	Hours of Operation	Technology Impact Distributions: Power Output	Technology Impact Distributions: Net Revenue
				

Table 6: Uncertainty Distributions Assigned to Noise Variables and Technology Impact Coefficients

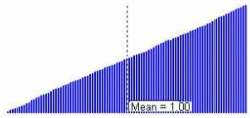
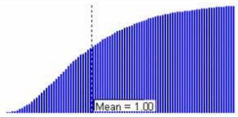
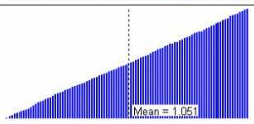
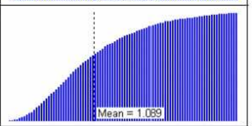
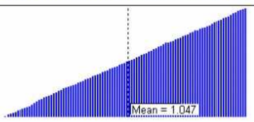
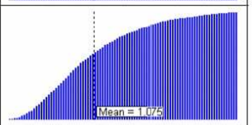
Configuration	Normalized Power Output	Normalized Net Revenue
1: Baseline		
2: Baseline + Technology 1		
3: Baseline + Technology 2		

Table 7: Cumulative Distribution Functions for Normalized Power Output and Normalized Net Revenue

Step 12: Select the Technologies with the Highest Probability of Success

For this demonstration, the resulting CDFs are displayed in Table 7. Here, the annual energy output and revenue are the only metrics of interest to the customer. It is evident which configuration is superior even before weighting the relative importance of the two metrics. The first technology not only boosts energy output and revenue above the baseline values, but also above the values obtained using the competing technology. The second configuration, which incorporates the first technology, is therefore the superior choice.

Verification: A Second Example

Though it is intuitive that temperature and humidity will have a significant effect on these example systems, it is still possible that there exists one optimal solution that should be employed for all operating conditions. Even so, this method can still be used to forecast the outputs that each customer can expect for the given operating conditions. Whatever the case may be, this methodology is applied to the same problem for drastically different operating conditions. The previous example demonstrated that the technologies are, in fact beneficial in a region with hot and arid operating conditions. Intuitively, it is evident that technology performance will be degraded in a cooler, more humid region, such as Seattle, Washington. The extent of this degradation can be approximated using the proposed method. A plot of the data points that make up the weather model for Seattle, Washington is shown in Figure 5.

In comparison to Figure 2, it is evident that Seattle, Washington is representative of the opposite extreme of the operating conditions found in Phoenix, Arizona. In addition, Figure 6 gives the outcome of step 8, a plot of power output versus temperature in Seattle. This figure is similar to Figure 3, except that the frame has shifted to reflect the cooler temperatures in Seattle, and some other slight differences are caused by the differing humidity trends. From Figure 6, it is evident that there are far more losses associated with technology performance in Seattle than in Phoenix. Although it may appear as though the technologies will still provide some benefit, the results will likely shift when the added uncertainties and risks are quantified. Indeed, when the full method is executed for Seattle, the final cu-

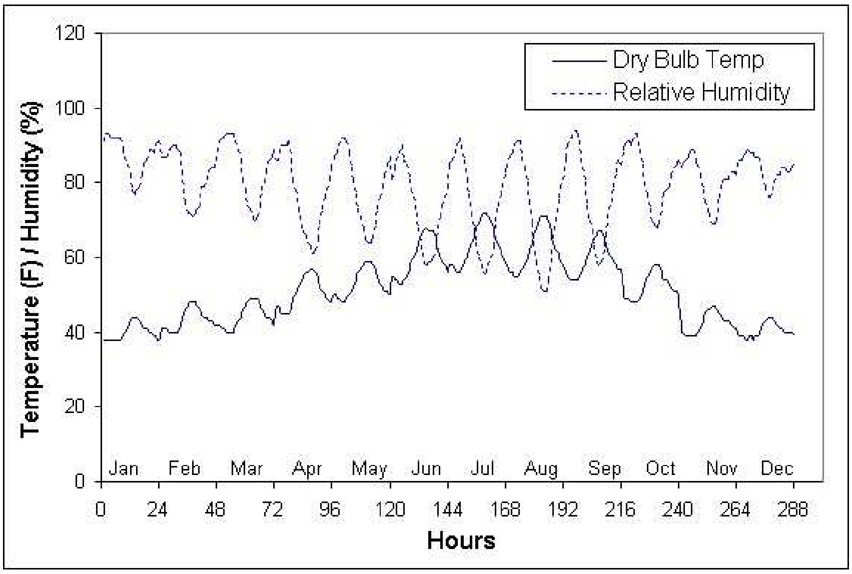


Figure 5: Annual Fluctuations in Temperature and Humidity in Seattle, Washington

mulative distributions actually show a small loss in power output and revenue when the second technology is installed. The first technology shows neither a benefit or a loss. Even though the first technology does not appear to ever hinder the system performance, it may not be in the manufacturer's best interest to install this technology in every system. The reason being that it not only costs extra money for the technology hardware, but that the technology addition causes a great deal of added uncertainty and risk. This additional uncertainty is an unwanted byproduct of new-technology infusion, and it should be avoided if the technology is not overly promising. Thus, in this situation the optimum configuration is the baseline design. The presence of two different optimum configurations for two different sets of operating conditions justifies the need for the demonstrated methodology. This example also demonstrates the importance of having the capability to reconfigure a system to best meet every customer's needs.

If it is deemed to be too much trouble to reconfigure every single system that is sold, the manufacturer may simply wish to define a set of configurations. For instance, this method could be used to define five separate configurations, each optimized for different operating conditions. As an example, the results from the evaluation for Phoenix could be used as a general solution for all locations with hot and arid operating conditions. The solution for Seattle might be a general solution for all cold and humid locations. In addition, there might be three other generalized solutions; one for a hot and humid location, one for a cold and arid location and one for moderate operating conditions. Then, a customer may be classified as falling under one of these categories, and the appropriate configuration would be sold to that customer. It is even likely that the optimal configuration may be the same for more than one of these groups. In that case, there may only be two or three optimized configurations.

There exists the possibility that, while operating conditions affect the system performance, they may not affect the outcome of the optimized configuration. If this were true, then yearly averages for the ambient conditions could be used to replace the 288-run ambient model that is used to model these conditions. Hence, if temperature and humidity are approximated using a single average value for each, would the optimum solution be the same? For this problem, the answer is no. The inlet conditioning technologies are designed such that they are only turned on when they will provide a benefit, and are turned off the remainder of the time. If the average annual temperature in a given region is above the point where the technology is turned on, then this approximation will give results that grossly overestimate the performance enhancements. Similarly, if the average annual temperature of a certain location is below the on / off switch for the technology, the approximation will show significant losses attributed to the technology, when, in fact, it may still provide some benefits. Thus, the results are far more reliable if the proposed method is used to model the operating conditions.

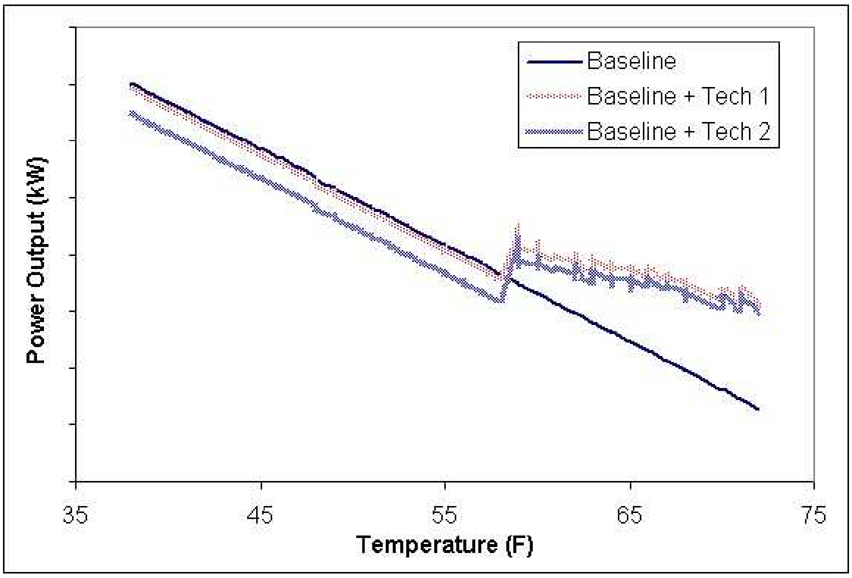


Figure 6: Power Output for a Range of Temperature and Humidity Values in Seattle, Washington

Conclusions

This paper presented a systematic approach for identifying and modeling coupled operational uncertainties, and forecasting those effects on system performance. The research focused on enhancing existing methods to capture the effects of operational uncertainty, specifically, the trends in ambient weather conditions. This paper illustrated how to model these coupled ambient trends, and how to integrate this model with other tools in order to optimize design settings, select promising technologies and / or forecast system performance in a given location. In a more general sense, the method enables a consideration of coupled noise variables. The results demonstrate the need for a more accurate depiction of operating conditions early in the design, and increased flexibility in the final design of systems that operate in volatile markets.

The approach has been tested on a power plant problem involving the selection of new technologies that propose to enhance performance during certain conditions. The results show that the optimal configuration varies with the location of operation. If one solution is employed for all operating conditions, it is likely that losses will incur in some of those locations. The proposed method aims to minimize these losses by forecasting operating conditions and identifying uncertainties, and assessing the resulting effects on the design space in order to pinpoint the optimum configuration.

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